Testing Decision Rules for Multiattribute Decision Making

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by

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Abstract

This paper investigates the existence of an editing phase and studies the compliance of subjects' behaviour with the most popular multiattribute decision rules. We observed that our data comply well with the existence of an editing phase, at least if we allow for a natural error rate of some 25%. We also found a satisfactory performance of certain groups of subjects for the conjunctive rule, for the elimination–by–aspects rule, for the majority rule, and for the maximin rule. Our data suggest, however, rejection of the prominence hypothesis and of the maximax rule. Thus, our experiment sheds light on the existence of an editing phase and on the use of various multiattribute decision rules.

Keywords: Sequential Decision Making, Editing Phase, Prominence Hypothesis, Elimination-by-Aspects Hypothesis, Conjunctive Decision Rule, Majority Rule, Multiattribute Decision Making.

Journal of Economic Literature classification: C91, D46, D80, A14.

1 Introduction

When we designed an experiment of sequential decision making to empirically investigate whether subjects satisfy the axiom of independence of irrelevant alternatives, we became increasingly suspicious of the usefulness of distinguishing between static and dynamic decision models. For a long time, psychologists have stressed that a single decision is the result of perceptual, emotional and cognitive processes, which all contribute to a dynamic process in which the decision maker seeks and evaluates information sequentially[1]. This insight led us soon to the question which decision rules are observed by subjects, or, to put it more precisely, which decision rules are not at variance with subjects' decisions. Fortunately, our experiment equipped us generously with data, which allowed us to embark on this research. In particular, we investigate the existence of an editing phase in which dominated alternatives are eliminated. Furthermore, we test several multiattribute decision rules for their explanatory power of consistency with subjects' choices.

Section 2 develops the theoretical underpinning of our paper. It starts by explaining the dynamics of decision making through decision makers' effort to minimize cognitive effort. Then we proceed to review the most important multiattribute decision rules. Section 2.3 examines whether decision processes are multi–phased.

Section 3 gives a detailed description of our experiment, and Section 4 contains the results of our study. Section 4 parallels Section 2 in its structure to facilitate the comparison of more theoretical considerations with the empirical evidence of our experiment. Section 5 concludes.

2 How to Simplify Decision Problems

2.1 Minimizing Cognitive Effort

A decision maker's task of seeking, gathering and evaluating information involves a considerable *cognitive effort* or cost of thinking[2]. As different decision rules may require different amounts of cognitive effort, decision makers who try to minimize the amount of cognitive effort will, during the decision process, tend to apply simpler rules before they try rules which require more cognitive effort[3].

Now, which decision rules can be assumed to be simpler rules in multiattribute decision making? Multiattribute decision rules can be divided into *noncompensatory* or noncommensurable and *compensatory* or commensurable decision rules. The distinction between these types of decision rules is straightforward. Under a noncompensatory rule, the abundance in some attribute cannot compensate for the deficiency in another. Under

[1] Cf., e.g., Montgomery and Svenson (1976), 283; Svenson (1979), 86.

[2] For an interesting theory of the cost of thinking cf. Shugan (1980). The cost of optimization was analysed by Conlisk (1988). Von Winterfeldt and Edwards (1982) and Harrison (1994) have blamed experimental economists for insufficient rewards used in their experiments, which were not attractive enough to compensate subjects for their decision cost. They argue that insufficient rewards could have been the cause for much observed falsification of correct theories. For a fully–fledged model of decision costs and subjects' performance in experiments cf. Smith and Walker (1993).

[3] Montgomery and Svenson (1976), 288f.; Svenson (1979), 107; Shugan (1980), 100; Russo and Dosher (1983).

a compensatory rule, trade offs among all attributes must be defined. A compensatory rule must state exactly which improvement in attribute k of a choice alternative just compensates for a given deterioration in attribute ℓ to keep the respective choice alternative equally attractive. Therefore, the attractiveness of a choice alternative under a compensatory decision rule is usually addressed as its *utility*[4].

Empirical work supports the "general conclusion that subjects find it rather difficult to weight and 'trade off' values in a compensatory manner. ... information that does not require 'in the head' transformation is preferred in the interest of cognitive economy.[5]" This empirical evidence has induced Slovic and MacPhillamy to suggest a *common–dimension effect* stating that attributes are weighted more heavily in the comparison of choice alternatives when they are common. On grounds of minimizing cognitive effort, subjects eschew making transformations of information prior to its use[6].

When trying to minimize cognitive effort, the decision makers may, of course, use a plurality of decision rules[7] rather than following the prescript of utility maximization as has been assumed by mainstream microeconomics. Empirical evidence has shown that some of the decision rules applied are used subconsciously and cannot easily be communicated[8], which, however, does not invalidate the use of a plurality of decision rules.

Empirical research has shown that decision makers apply decision rules sequentially in order of increasing cognitive effort. This means that they use first noncompensatory rules to whittle down the number of choice alternatives by eliminating alternatives, thereby simplifying the decision task considerably. Compensatory decision rules are subsequently used to analyse the simplified decision problem. Indeed, noncompensatory rules are applied to decision problems with many alternatives whereas compensatory rules dominate in decision problems with only few choice alternatives[9]. Let us illustrate this with a quotation of Payne. He argues that "the less cognitively demanding decision procedures, conjunctive and elimination–by–aspects, might be called early in the decision process as a way of simplifying the decision task by quickly eliminating alternatives until only a few alternatives remained as choice possibilities. The subject might then employ one of the more cognitively demanding choice procedures ...[10]" Many other authors have followed him in perceiving individual choice procedures as multi–staged processes[11].

These considerations describe nothing more than a general pattern of sequential deci-

[4] Montgomery and Svenson (1976), 285.

[5] Slovic and MacPhillamy (1974), 193.

[6] Cf., e.g., Slovic and MacPhillamy (1974); Slovic and Lichtenstein (1968); Payne and Braunstein (1971). Notice that Slovic and MacPhillamy's common–dimension effect is similar to Slovic and Lichtenstein's *compatibility effect*.

[7] Keen (1977), 33.

[8] Cf. Bem (1972); Nisbett and Wilson (1977); Fischhoff, Slovic, and Lichtenstein (1980). Contrary to these views cf. Smith and Miller (1978) and White (1980).

[9] Cf. Payne (1976), 382; Russo and Dosher (1983); Johnson and Meyer (1984).

[10] Payne (1976), 384f.; cf. also Payne (1982), 398f.

[11] Cf., e.g., Simon (1955); MacCrimmon (1968b); Mintzberg, Raisinghani and Théorêt (1976); Montgomery and Svenson (1976); Nisbett and Wilson (1977); Wright and Barbour (1977); Kahneman and Tversky (1979), 274ff.; Svenson (1979); Tversky and Sattah (1979), 542f.; Shugan (1980); Montgomery (1983), 350ff.; Russo and Dosher (1983); Dawes (1988), chapter 4; Tversky, Sattah and Slovic (1988), 372.

sion making. Subjects may, however, follow different decision rules. Some subjects may be more attracted by particular decision rules, others may be more attracted by others. In this study, we investigate first whether decision processes are multi–phased where a rough screening applies at the outset of a decision problem, and second which decision rules are capable of explaining the actual decisions of palpable groups of subjects.

In the rest of this section, we will first consider a menu of rules for multiattribute decision making. Then we shall investigate whether individual decision processes indeed consist of several phases which can be clearly discerned.

2.2 A Menu of Decision Rules

In this section we shall concisely characterize the most important multiattribute decision rules[12]. As to the notation, let $A := \{a_i \mid i = 1, 2, \ldots, n\}$ denote the set of decision alternatives a_i, let $D := \{d_k \mid k = 1, 2, \ldots, K\}$ denote the set of attributes, and let a_{ik} denote the level of attribute k in the decision alternative i. A decision alternative is thus defined by a vector of attribute levels, i.e. $a_i = (a_{i1}, a_{i2}, \ldots, a_{iK})$. Moreover, let $a_i > a_j$ denote that *all* components of a_i are greater than the respective components of a_j, $a_i \geqq a_j$ that *no* component of a_j is greater than the respective component of a_i, and let $a_i \geq a_j$ denote that $(a_i \geqq a_j) \& \neg(a_i = a_j)$. The weak preference relation between choice alternatives is denoted by $\succsim$, $\succ$ and $\sim$ being its asymmetric and symmetric components. For $A' \subseteq A$, $E(A')$ denotes the set of alternatives which have not been eliminated by some decision rule.

2.2.1 Noncompensatory Decision Rules

The most important noncompensatory decision rules are the dominance rule, the conjunctive rule, the disjunctive rule, and the lexicographic rule with its variations.

(1) Dominance rule:

$$a_i \geq a_j \Rightarrow a_i \succ a_j;$$

$$E(A) = \{a_i \in A \mid \nexists\, a_j : a_j \geq a_i\}.$$

The dominance rule declares a_i as superior to a_j, if a_j has no better attribute level than a_i, but a_i outperforms a_j with respect to at least one attribute. The dominance rule provides for pruning the set of feasible choice alternatives by eliminating those choice alternatives which happen to be dominated by some other choice alternatives. It seems to be a generally–agreed–upon decision rule. Notice, however, that it can (save for rather special causes) only shrink the set of viable choice alternatives without being able to single out a best one.

(2) Conjunctive rule:

$$a_i \geqq c \text{ and } \exists\, k \text{ such that } a_{jk} < c_k \Rightarrow a_i \succ a_j;$$

[12] Cf., e.g., Coombs and Kao (1955); Coombs (1964); Dawes (1964); Montgomery and Svenson (1976), 285ff.; Fishburn (1978); Svenson (1979), 89ff.; Shugan (1980), 100.

$$E(A) = \{a_i \in A \mid a_i \geqq c\},$$

where $c = (c_1, c_2, \ldots, c_K)$ is a vector of minimum attribute levels to be satisfied by eligible choice alternatives. A conjunctive rule is thus a multidimensional generalization of the satisficing principle suggested by Simon (1955). It requires any eligible choice alternative to satisfy certain minimum standards for all attributes.

In other words, this means that a conjunctive rule evaluates choice alternatives on their least relevant attributes. Dawes has provided a good instance for a conjunctive rule: "For example, in order to stay alive an individual must have every vital organ functioning above a certain level (by definition). The fact that a given individual has an excellent liver, heart, and lungs will not compensate for the fact that a doctor has just removed his single kidney; an individual may have radically inferior organs, but he will not die unless one ceases to function above a minimum level. Life or death depends upon one's worst vital organ.[13]" Notice that a conjunctive rule can, like a dominance rule, serve merely as a selection procedure which narrows down the set of eligible choice alternatives. It can, however, also be shaped as a choice rule which directly determines the optimum choice alternative. This is accomplished by varying the vector of minimum attribute levels until only one choice alternative passes all requirements.

(3) Disjunctive rule:

$$\exists\, k \text{ such that } a_{ik} \geq c_k \text{ and } a_j < c \Rightarrow a_i \succ a_j\ ;$$

$$E(A) = \{a_i \in A \mid \exists a_{ik} \geq c_k \text{ for some } k = \{1, 2, \ldots, K\}\}\ ,$$

where $c = (c_1, c_2, \ldots, c_K)$ is a vector of attribute levels of which at least one has to be satisfied. A disjunctive rule thus requires any eligible choice alternative to satisfy certain minimum standards for *at least one* attribute. This means that a disjunctive rule evaluates choice alternatives on their greatest merits. If the choice alternatives happen to be candidates to fill some very special position, then they are evaluated according to their greatest talents regardless of their other attributes[14]. A disjunctive rule can, like a dominance rule, serve only as a screening device which whittles down the set of eligible choice alternatives. Raising the c's sufficiently it can also be sharpened to isolate a single best choice alternative. Then it comes close to a lexicographic rule.

(4) Lexicographic rule:

Let d' denote a vector of attributes $d_k,\ k = 1, 2, \ldots, K$, arranged in decreasing importance of the attributes, i.e. d'_m is considered to be more important than d'_ℓ if $m < \ell$.

$$\begin{aligned} a_{im} &= a_{jm},\ a_{i\ell} > a_{j\ell} \quad \text{for all } m,\ 1 \leq m < \ell, \\ &\text{and for some } \ell = 1, 2, \ldots, K' \Rightarrow a_i \succ a_j; \end{aligned}$$

[13] Dawes (1964), 105. Cf. also Einhorn (1970), 223; Einhorn (1971), 14f.; Montgomery and Svenson (1976), 285; Payne (1976), 367; Wright and Barbour (1977), 94f.; Svenson (1979), 89.

[14] Cf. Dawes (1964), 105; Einhorn (1970), 223; Montgomery and Svenson (1976), 285; Svenson (1979), 89.

$$E(A) = \{a_i \in A \mid \nexists\, a_j : a_{jm} = a_{im},\ a_{j\ell} > a_{i\ell} \text{ for all } m, \\ 1 \leq m < \ell \text{ and for some } \ell = 1, 2, \ldots, K'\}.$$

A lexicographic rule declares a_i as superior to a_j, if a_i has a better attribute level than a_j in the most important attribute for which the attribute levels differ. The lexicographic rule has spawned many offshoots, such as the lexicographic semiorder rule[15], the elimination–by–aspects (EBA) rule[16], the constant–ratio (CR) rule[17], the elimination–by–tree (EBT) and the hierarchical elimination (HE) rules[18] (which happen to be equivalent), and the prominence hypothesis[19] (PH).

The *elimination–by–aspects hypothesis* was pioneered by Restle and Shepard[20]. Building upon their work, Tversky developed a theory describing choice as an elimination process governed by successive selection of aspects or attributes proceeding in the order of their importance[21]. He illustrates this with the following example: "In contemplating the purchase of a new car, ... the first aspect selected may be automatic transmission: this will eliminate all cars that do not have this feature. Given the remaining alternatives, another aspect, say a $3000 price limit, is selected and all cars whose price exceeds this limit are excluded. The process continues until all cars but one are excluded.[22]" Adhering to the (then dominating) conception of choice as a stochastic phenomenon[23], Tversky conceived of evaluation functions of the various aspects (or attributes) of choice alternatives and modelled the choice probabilities of the various alternatives as increasing functions of the values of the relevant aspects. As the values of the various aspects are, however, not known a priori, Tversky chose an experimental design presenting the same stimuli repeatedly to his subjects.[24] This provided him with choice frequencies of the decision alternatives which he could use for the estimation of the values of the aspects.[25]

Because of considerable data requirements of the elimination–by–aspects rule, Tversky and Sattah later developed a hierarchical elimination process which is more parsimonious with respect to data than the former one[26]. This *elimination–by–tree rule* or *hierarchical elimination rule* is applicable whenever the decision problem is presentable in the form of a decision tree in which the decision maker eliminates various subsets of alternatives sequentially according to some hierarchical structure. The choice behaviour is assumed to be context dependent, i.e. driven by the preferences among the various attributes. The

[15]Tversky (1969).
[16]Tversky (1972a,b).
[17]Luce (1959; 1977).
[18]Tversky and Sattah (1979).
[19]Tversky, Sattah, and Slovic (1988).
[20]Restle (1961); Shepard (1964a,b).
[21]Tversky (1972a,b).
[22]Tversky (1972a), 285.
[23]Cf. Luce (1958; 1959); Block and Marschak (1960); Chipman (1960); Marschak (1960); Becker, DeGroot, and Marschak (1963a,b). It was mainly Debreu's (1960) critique of Luce (1959), which prompted Tversky's (1972a,b) work.
[24]Tversky (1972a), 292.
[25]Tversky (1972a), 293f.
[26]Tversky and Sattah (1979).

main significance of this model seems to be its greater parsimony with respect to data requirements. Its basic message is not different from the elimination–by–aspects rule.

The *prominence hypothesis* suggested by Tversky, Sattah and Slovic[27] is some kind of truncated lexicographic rule. It draws on Slovic's *more–important–dimension hypothesis*[28]. Carrying out four experiments, he observed "that people resolve choices between equally valued, multiattribute alternatives by selecting the alternative that is superior on the more important attribute or dimension.[29]" Slovic's early work later induced the development of the prominence hypothesis. It says essentially that the more prominent attribute will weigh more heavily in choice. This suggests that, in a way, the prominence hypothesis endeavours to materially establish the preference order of attributes which would eventually define a lexicographic rule. It seems, however, that the formulation of the prominence hypothesis has not progressed far beyond the two–attribute world[30]. When discussing their results, Tversky, Sattah, and Slovic stress the necessity of further investigations into the prominence hypothesis: "Although the prominence effect was observed in a variety of settings using both intrapersonal and interpersonal comparisons, its boundaries are left to be explored. How does it extend to options that vary on a large number of attributes? ...With three or more attributes ... additional considerations may come into play. For example, people may select the option that is superior on most attributes ... In this case, the prominence hypothesis does not always result in a lexicographic bias."[31]

2.2.2 Compensatory Decision Rules

I) Without interattribute comparability

(5) Majority rule[32]:

$$\begin{aligned}&\#\{a_{ik} \mid a_{ik} > a_{jk},\ k = 1, 2, \ldots, K\}\\ &\qquad > \#\{a_{ik} \mid a_{ik} < a_{jk},\ k = 1, 2, \ldots, K\} \Rightarrow a_i \succ a_j;\end{aligned}$$

$$\begin{aligned}E(A) \quad = \quad &\{a_i \in A \mid \nexists\ a_j : \#\{a_{jk} \mid a_{jk} > a_{ik},\ k = 1, 2, \ldots, K\}\\ &> \#\{a_{jk} \mid a_{jk} < a_{ik},\ k = 1, 2, \ldots, K\}\}.\end{aligned}$$

[27]Tversky, Sattah, and Slovic (1988), 372.

[28]Slovic (1975), 281.

[29]Slovic (1975), 286.

[30]Notice that Tversky, Sattah, and Slovic (1988), 376 and 380ff., use the prominence hypothesis in conjunction with the compatibility principle to explain the *preference reversal phenomenon* [for details cf. Lichtenstein and Slovic (1971)]. According to the compatibility principle, "the weight of any input component is enhanced by its compatibility with the output. ...For example, the pricing of gambles is likely to emphasize payoffs more than probability because both the response and the payoffs are expressed in dollars." [376]

[31]Tversky, Sattah, and Slovic (1988), 383.

[32]Russo and Dosher (1983), 683, call this rule *majority of confirming dimensions*.

The majority rule mimics the old wisdom that more arguments in favour of an alternative are better than less arguments. It assumes that subjects just count attributes in favour of the respective alternatives and opt for that one which has more attributes on its side. This decision rule may violate transitivity and is thus not immune to preference cycles. This means that there may well exist $A' \subseteq A$ such that $E(A') = \emptyset$.

II) With interattribute level comparability

(6) Maximin rule:

$$\min_k{}^*\{a_{ik}\} \succ \min_k{}^*\{a_{jk}\} \Rightarrow a_i \succ a_j;$$

$$E(A) = \{a_i \in A \mid \nexists\ a_j : \min_k{}^*\{a_{jk}\} \succ \min_k{}^*\{a_{ik}\}\}.$$

(7) Maximax rule:

$$\max_k{}^*\{a_{ik}\} \succ \max_k{}^*\{a_{jk}\} \Rightarrow a_i \succ a_j;$$

$$E(A) = \{a_i \in A \mid \nexists\ a_j : \max_k{}^*\{a_{jk}\} \succ \max_k{}^*\{a_{ik}\}\}.$$

The asterisks at min and max indicate that the minimization or maximization occurs with respect to *preferences* among attributes, because attributes may have different dimensions which cannot be directly compared. Alternatively, we can use (partial) utilities defined on the various attributes. Notice that the maximin rule is an extension of the conjunctive rule and the maximax rule is an extension of the disjunctive rule if interattribute level comparability holds[33].

III) With cardinal interattribute comparability

(8) Linear multiattribute utility rule:

$$\sum_{k=1}^{K} w_k\ v_k(a_{ik}) > \sum_{k=1}^{K} w_k\ v_k(a_{jk}) \Rightarrow\ a_i \succ a_j;$$

$$E(A) = \{a_i \in A \mid a_i \in \arg\max_j\{\sum_{k=1}^{K} w_k\ v_k(a_{jk})\}\},$$

where the w_k's denote the weights of the attributes and the $v_k(\cdot)$'s denote the conditional value functions of the attributes. The linear multiattribute utility rule plays a prominent role in models of multiattribute decision making[34]. It has given rise to other developments

[33]Shugan (1980), 100, neglects this requirement. There is also confusion about this condition in Dawes' (1964) article.

[34]Cf., e.g., Yntema and Torgerson (1961); for a good survey up to the seventies cf. Slovic and Lichtenstein (1971), in particular 677ff. For later surveys cf. Weber and Borcherding (1993) and Borcherding, Schmeer, and Weber (1995). For the rigorous establishment of the linear multiattribute utility rule cf. Farquhar (1977) and Dyer and Sarin (1979).

such as the use of the Minkowski metric and the generalized mean.

(9) Multiplicative utility rule:

$$\prod_{k=1}^{K}[1+\lambda w_k\ v_k(a_{ik})] > \prod_{k=1}^{K}[1+\lambda w_k\ v_k(a_{jk})] \Rightarrow a_i \succ a_j;$$

$$E(A) = \{a_i \in A \mid a_i \in \arg\max_j\{\prod_{k=1}^{K}[1+\lambda w_k\ v_k(a_{jk})]\}\},$$

where λ is a general scaling factor[35]. Einhorn has used offshoots of the multiplicative utility rule to mimic a conjunctive rule by

$$\prod_{k=1}^{K}(a_{ik})^{\beta_k}\ ,$$

and a disjunctive rule by

$$\prod_{k=1}^{K}\frac{1}{(c_k - a_{ik})^{\beta_k}}\ ,$$

pretending that these functional forms are noncompensatory rules[36]. However, inspection shows that these are in fact compensatory rules. Rather than approximating conjunctive or disjunctive rules, the former can approximate a maximin rule, and the latter a maximax rule.

2.3 Are Decision Processes Multi–Phased?

When testing the hypothesis that decision processes are multi–phased, we should preferably focus on the simplest possible and largely undisputed case. This seems to be the hypothesis that the first part of decision processes consists of an *editing phase* in which dominated alternatives are eliminated from further consideration. Among noncompensatory decision rules, the dominance rule is certainly the least demanding and the most convincing one. It is not sensible to choose an alternative which is in no respect better, but for some attributes strictly worse than some other choice alternatives.

This hypothesis was made particularly lucid by Kahneman and Tversky (1979). In their prospect theory, they distinguished two phases in a choice process: "an early phase of editing and a subsequent phase of evaluation. The editing phase consists of a preliminary analysis of the offered prospects, which often yields a simpler representation of these prospects. In the second phase, the edited prospects are evaluated and the prospect of highest value is chosen. ... The function of the editing phase is to organize and reformulate the options so as to simplify subsequent evaluation and choice. Editing consists of the

[35] Cf. Keeney (1974).

[36] Einhorn (1970), 227; Einhorn (1971), 3.

application of several operations that transform the outcomes and probabilities associated with the offered prospects.[37]" One of the major operations of the editing phase is the *detection and elimination of dominated alternatives*[38]. Kahneman and Tversky maintain that "dominated alternatives ... are rejected without further evaluation.[39]"

These considerations, taken from decision making under risk, readily carry over to multiattribute decision making under certainty. In this field, too, many scholars have argued in favour of multi–staged decision processes whose early stages consist of a screening phase (preceeding the evaluation phase proper), in which alternatives are eliminated from the option set following some noncompensatory decision rule[40]. The most fundamental elimination procedures in the screening or editing phase should obviously encompass the dominance rule. As this rule seems to be the only undisputed elimination rule[41] in the editing phase, we restrict ourselves to testing whether an editing phase exists in which the dominance rule applies.

In the course of our experiment, we, therefore, investigate whether dominated alternatives are really eliminated from the choice set. As the possibility cannot be ruled out that also undominated alternatives are eliminated in the screening phase, we will focus on searching the subjects' short lists of alternatives for dominated alternatives. Taking up a suggestion of Farquhar and Pratkanis, we will consider the structure of our subjects' short lists with respect to k–dominated alternatives, which means that exactly k options dominate the respective alternative[42] in a subject's short list. In this terminology, undominated alternatives are referred to as 0–dominated alternatives.

3 The Experiment

3.1 Stimulus Material

The stimulus was an evaluation sheet of the data of 25 applicants for the position of a chief secretary to be hired. The subjects were told that they should imagine themselves to be successful entrepreneurs and, since they were short of time, they entrusted the screening of the applicants for this position to a professional recruitment agency. The recruitment

[37] Kahneman and Tversky (1979), 274.

[38] This assumption is also necessary to immunize prospect theory against violations of stochastic dominance. Cf. Kahneman and Tversky (1979), 284: "Direct violations of [stochastic] dominance are prevented, in the present theory, by the assumption that dominated alternatives are detected and eliminated prior to the evaluation of prospects." Notice that cumulative prospect theory avoids this problem; cf. Tversky and Kahneman (1992).

[39] Kahneman and Tversky (1979), 275. Notice that the rejection of dominated alternatives has been stated by MacCrimmon (1968a), 15–17, as his third postulate of rational choice. In this empirical investigations, MacCrimmon reports some violation of this postulate, but adds that, in the interview after the experiment, all subjects repealed their violations of MacCrimmon's third postulate, attributing the violations to "carelessness in their reading or thinking about the problem".

[40] Cf. the references in footnote 11.

[41] Montgomery (1983) has ventured to model decision processes in which decision makers apply first transformations of the alternatives' attributes in order to render the dominance rule applicable even in such cases in which there was no dominance in the primary data.

[42] Farquhar and Pratkanis (1993), 1223.

agency assigns a code number to each applicant and evaluates the applicants with respect to six attributes, viz.[43]:

(i)	IQ ...	quotient of intelligence defined with a mean value 100, a standard deviation of 15, and the assumption that intelligence is normally distributed;
(ii)	ST ...	proficiency in shorthand and typewriting to be measured along a scale ranging from 1 to 100 points;
(iii)	L ...	proficiency in foreign languages measured as a weighted index (the weights reflecting the needs of the firm) along a scale ranging from 1 to 100 points;
(iv)	AM ...	appearance and good manners of an applicant measured along a scale ranging from 1 to 10 points;
(v)	EXP/PROF ...	experience and proficiency in office work measured along a scale ranging from 1 to 10 points;
(vi)	COMP ...	proficiency in working with personal computers, measured along a scale ranging from 1 to 10 points.

The *basic* evaluation sheet is depicted as Table 1. It exhibits a simple structure. The applicants numbered 1 and 2 excel with respect to the first attribute, where alternative a_1 dominates alternative a_2, although alternative a_2 is, in general, rather similar to alternative a_1. Moreover, alternative a_1 is 0–dominated (undominated), whereas alternative a_2 is 1–dominated (by alternative a_1), so that, when alternative a_1 drops out, alternative a_2 becomes a 0–dominated alternative and can replace alternative a_1 as some kind of a similarly structured second best alternative. This pattern is repeated for the six pairs of alternatives a_1 to a_{12}.

Alternative a_{13}, too, is 0–dominated. It is constructed such that the values of all its attributes are third best. For instance, only alternatives a_1 and a_2 have better values for the first attribute, only alternatives a_3 and a_4 have better values for the second attribute, and so on for all attributes.

The remaining alternatives a_{14} to a_{25} are at least 2–dominated. All are dominated by a_{13} and by at least one alternative of the first twelve alternatives. For example, a_{14} is dominated by a_{13} and a_1; a_{15} and a_{20} are dominated by 10 alternatives each; etc. The dominance structure is shown in Table 2.

This structure of choice alternatives as exhibited in the basic evaluation sheet is, of course, too revealing in this form to be presented to the subjects. Therefore, we employed a randomization of the lines of Table 1 and presented an evaluation sheet with randomly permutated lines to our subjects. (Notice that the chosen randomization was the same for all subjects.) As we wanted to eliminate biases from data presentation[44], we chose

[43]There is evidence that there is some effect of attribute ranges on attributes' weights in multiattribute decision making; cf. von Nitzsch and Weber (1993). However, we see no possibility to control for these effects. We could hardly do more than keeping attribute ranges constant for the two parts of the experiment.

[44]Cf., e.g., Montgomery and Svenson (1976), 287; Bettman and Kakkar (1977), 234; Svenson (1979), 99; Payne (1982), 391; Russo and Dosher (1983), 677; Johnson and Meyer (1984), 531ff. and 538.

Table 1: Basic Evaluation Sheet

Appl. No.	IQ	ST	L	AM	EXP/ PROF	COMP
1	120	70	75	6	8	6
2	118	65	73	5	7	5
3	95	90	67	8	7	8
4	94	88	66	8	7	7
5	97	68	95	8	6	8
6	96	66	92	7	5	8
7	101	72	59	10	8	6
8	100	69	57	9	7	5
9	104	75	72	8	10	7
10	103	73	69	8	9	7
11	108	81	62	6	7	10
12	107	79	60	6	7	9
13	109	85	82	8	8	8
14	105	62	70	5	7	6
15	91	59	62	5	7	5
16	88	81	55	8	7	5
17	79	66	64	7	6	6
18	92	57	80	6	5	7
19	88	63	50	7	4	5
20	96	60	55	6	6	4
21	99	48	52	5	6	5
22	100	71	65	7	7	7
23	102	66	48	6	6	7
24	96	75	51	5	4	8
25	104	62	46	6	7	5

the matrix form of data presentation, as this mode had proved to engender the least distortions[45].

For the second part of the experiment, we told subjects that, after several years, the chief secretary has been transferred to support the establishment of a new branch of the firm, and a new secretary was to be hired. As the recruitment agency had performed well, it is again entrusted with the evaluation of the applicants. For the second part, we used essentially the same set of alternatives. In order to camouflage this fact, we employed a different randomization of the lines, and re–arranged the columns, using AM as the first attribute, IQ as the second, EXP/PROF as the third, L as the fourth, COMP as the fifth, and ST as the sixth. We explained the re–arrangement of columns by telling the subjects that the recruitment agency had changed its evaluation reports so as to enlist the features which concern an applicant's personality in the first places, and the more

[45]Cf. the third experiment of Bettman and Kakkar (1977), as well as Russo (1977).

Table 2: The Dominance Structure of the Choice Alternatives

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	$\sum$
1	-	1	-	-	-	-	-	-	-	-	-	-	-	1	1	-	-	-	-	1	1	-	-	-	1	6
2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	1	-	-	-	-	2
3	-	-	-	1	-	-	-	-	-	-	-	-	-	-	1	1	1	-	1	-	-	-	-	-	-	5
4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	1	-	1	-	-	-	-	-	-	4
5	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	1	1	1	1	-	-	-	-	-	5
6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	-	-	-	-	-	-	2
7	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	1	1	1	-	-	-	-	4
8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	1	-	-	-	-	3
9	-	-	-	-	-	-	-	-	-	1	-	-	-	-	1	-	1	-	1	1	1	1	1	-	1	9
10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	1	-	1	1	1	1	1	-	-	7
11	-	-	-	-	-	-	-	-	-	-	-	1	-	-	1	-	-	-	-	1	1	-	1	1	1	7
12	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	-	1	1	1	5
13	-	-	-	-	-	-	-	-	-	-	-	-	-	1	1	1	1	1	1	1	1	1	1	1	1	12
14	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	1	-	-	-	-	2
15	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
16	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-	1
17	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
18	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
19	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
20	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
21	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
22	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	1	-	1	1	1	-	-	-	-	5
23	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
24	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
25	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
$\sum$	0	1	0	1	0	1	0	1	0	1	0	1	0	2	10	3	7	3	11	10	11	3	5	3	5	-

1 means that alternative i (line) dominates alternative j (column). The line sums indicate the number of alternatives which are dominated by the alternative of the respective line. The column sums indicate the number of alternatives which dominate the alternative of the respective column (k–dominance).

technical properties only thereafter. Moreover, one or two of the previous alternatives (to be explained in the next section) were deleted, so that a subject was presented an evaluation sheet containing 23 or 24 of the original 25 alternatives of the first part of the experiment, arranged, however, in a different order.

3.2 Response Method

Several days before the start of the first part of the experiment, the subjects were introduced to the problem (i.e., recruitment of a chief secretary) and received the agency's evaluation sheet (i.e., a randomized version of Table 1). They were told that they should carefully analyze it and think about a short list of candidates, about the candidate who should be chosen to be employed, and about the relative importance of the various attributes. Furthermore, subjects were asked to enter their names in a time–table and to show up at the agreed time for the first part of the experiment.

The experiment was administered on a computer. The subjects first entered their personal data to enable us to join the individual responses of the first and the second part of the experiment. Then the subjects were asked to order the six attributes according to their importance. They could state indifference as well as strict preference. We then asked the subjects for the short lists of their most preferred candidates. They could nominate up to ten candidates. Then we asked the subjects to state which candidate they wanted to hire. After the respective response, the subjects were told that the chosen candidate had just recently withdrawn her or his application. The subjects should kindly make another choice. After having done that, the subjects were informed that this very candidate had meanwhile accepted another offer and was, therefore, no longer available. They were told that the recruitment agency had assured that all of the remaining candidates were still available. The subjects should kindly accept the agency's apologies and make one more choice. This concluded the first part of the experiment. It provided us with data on subjects' short lists and with data on three actual decisions made for each subject.

We then prepared a second evaluation sheet as described above. The first best alternative of the first choice was the one to be deleted. As we expected a distinct preference for alternative a_{13}, we deleted also this alternative, if a_{13} happened to be the first or second best alternative in the first part of the experiment. If the alternative a_{13} emerged as first best, then the second best alternative, too, was eliminated. Then the subjects were invited to indicate the short lists of their most preferred candidates (up to ten) and the candidates to be hired with first and second priorities.

As the second part of the experiment started only some two weeks later[46], and, as the second evaluation sheet was sufficiently camouflaged, we expected our subjects to feel as if they had to deal with a separate choice problem. The second part of the experiment provided us again with data on subjects' short lists and with data on two decisions made for each subject.

3.3 Procedure

The subjects were 45 students of the University of Kiel, mostly students of Economics, in their third or fourth year.

The subjects were introduced to the experiment on December 15 and 16, 1994, respectively, and received the first evaluation sheet. At the same time, they entered their names into a time–table, which allowed them 15 minutes at the computer. The first part of the experiment took place in the time period between December 19 and December 22, 1994, which left them more than a weekend to thoroughly analyze the choice problem before answering our questions. We then processed the second evaluation sheet, which started from a common re–arrangement of columns and another common randomization of lines[47]. Furthermore, the evaluation sheets were individualized by deleting the subjects first best alternative of the first part of the experiment and also the alternative a_{13} if it had been chosen as the second best alternative. If the alternative a_{13} emerged as first best, then the second best alternative, too, was eliminated. Then these individualized evaluation sheets were re–numbered (carrying now 23 or 24 applicants) and were sent by mail to the subjects' private addresses on December 29, 1994. This left them ample time to analyze the second evaluation sheet. The second part of the experiment took place in the time period between January 4 and 6, 1995.

All subjects were promised at least 10 Deutsch Marks as an honorarium for their efforts of participation in the experiment, provided that they had not given obviously absurd answers, which would indicate their carelessness in treating this experiment. This proviso was made with the intention to induce the subjects to undergo a thorough and

[46]We chose this short spell to exclude major changes of preferences, which would have invalidated the results gained from our experiment.

[47]This common basic structure of the evaluation sheets of the second part of the experiment was used to keep possible framing effects to their minimum.

earnest analysis of the choice problem before making their choices. Indeed, it had not proven to be necessary to deny a subject his or her honorarium. We finally paid the subjects 12 Deutsch Marks each for their participation.

There is a widespread conviction[48] that experiments should conform with Smith's precepts, in particular with saliency and dominance[49]. *Saliency* requires that subjects are guaranteed the right to claim a reward which is increasing (decreasing) in good (bad) outcomes of an experiment. *Dominance* requires that the reward structure dominates any subjective cost associated with participation in the experiment. Whereas these precepts are largely undisputed for experiments with outcomes with a natural priority order (i.e., more money is better than less), it is dubious for experiments in which respecting undiluted individual preferences is vital. Otherwise, the reward scheme would distort subjects' behaviour in favour of the values imposed by the experimenter's reward scheme. This led us to pay our subjects a fixed honorarium. We could have linked it with subjects' effort, e.g., design it as a fixed payoff per time unit, but we could not exclude other distortions of such a reward schedule. As we were fortunate enough to have interested our subjects in the experiment, and, as we felt that we owe our subjects some reward in return for their effort, we relied on the combination of subjects' interest and a moderate lump sum reward. In spite of the modesty of the financial reward, all subjects participated in both parts of the experiment, which demonstrates their vivid interest in our experiment.

There is, finally, the problem of the reliability of our data. Subjects are notoriously susceptible to mistakes and errors in their responses. For instance, "they could misunderstand the nature of the experiment; they could press the wrong key by accident; they could be in a hurry to finish the experiment; they could be motivated by something other than maximizing the welfare from the experiment *per se*.[50]" There have been several attempts to measure subjects' natural error rates[51]. They suggest a natural error rate of 15–25%, Camerer's 31.6% and Battalio, Kagel and Jiranyakul's less than 5% being, as it seems, outlyers. As to the error rate of our data we feel that Table 6 below would provide some good clues. If we take the failure to choose undominated alternatives in the ultimate decisions as our natural error rate, this gives us $\frac{12}{45} = 26,67\%$. If we take the failure to choose alternatives which have been nominated as members of the short lists, we get a natural error rate of $\frac{7}{45} = 15,56\%$. These two figures delineate pretty well the interval of commonly recognized error rates.

[48]Cf., e.g., Harrison's (1994) recent paper.
[49]Cf. Smith (1982), 931 and 934.
[50]Hey and di Cagno (1990), 292.
[51]Cf., e.g., Camerer (1989), 81; Starmer and Sugden (1989), 170; Battalio, Kagel, and Jiranyakul (1990), 47, note 13; Harless and Camerer (1994), 1263; Hey and Orme (1994), 1296, 1318, and 1320f.

4 Results

4.1 Testing the Editing Phase and the Elimination of Dominated Alternatives

Kahneman and Tversky (1979) and many other authors[52] have claimed that decision makers approach a decision problem in two phases. In the first, the so–called editing or screening phase, they simplify the decision problem, and in the second phase, the evaluation phase proper, they finally select the choice to be made. One of the more prominent features of the editing or screening phase is the elimination of all dominated alternatives.

We shall, therefore, test whether the short lists did not exceed the set of undominated alternatives and whether dominated alternatives were in fact eliminated by our subjects in a preliminary phase of solving the posed decision problem. In the first part of our experiment, there are exactly seven undominated alternatives (i.e. the odd–numbered alternatives from a_1 to a_{13}), six 1–dominated alternatives (i.e. the even–numbered alternatives from a_2 to a_{12}), and twelve k–dominated alternatives with $k \geq 2$ (i.e. the alternatives with numbers from a_{14} to a_{25}). In the second part of the experiment, there are at least six undominated alternatives, at least four 1–dominated alternatives, and at least eleven k–dominated alternatives with $k \geq 2$.

Table 3: Dominance Structure of the Short Lists (Part One)

Number of dominated alternatives in the short lists	Number of alternatives in the short lists										
	1	2	3	4	5	6	7	8	9	10	sum
0	0	1	3	2	0	0	1	–	–	–	7
1	0	0	4	3	3	2	0	0	–	–	12
2	–	0	1	0	4	0	1	1	2	–	9
3	–	–	0	0	0	0	3	2	1	4	10
4	–	–	–	0	0	0	1	2	0	3	6
5	–	–	–	–	0	0	0	0	0	1	1
6	–	–	–	–	–	0	0	0	0	0	0
7	–	–	–	–	–	–	0	0	0	0	0
8	–	–	–	–	–	–	–	0	0	0	0
9	–	–	–	–	–	–	–	–	0	0	0
10	–	–	–	–	–	–	–	–	–	0	0
sum	0	1	8	5	7	2	6	5	3	8	45

We have two groups of data to test the hypothesis of the elimination of dominated

[52] See the references in footnote 11.

alternatives, viz. the subjects' short lists and their choices made.

We consider first the subjects' short lists. The results are displayed in Table 3 for the first part of the experiment, and in Table 4 for the second. In the columns of these tables we list the number of alternatives in the respective short lists, in the rows the number of dominated alternatives in the short lists (irrespective of the degree of domination). Of course, there cannot be more dominated alternatives than the respective numbers of alternatives in the short lists, which means that there are only blanks in Tables 3 and 4 below their main diagonals.

Table 4: Dominance Structure of the Short Lists (Part Two)

Number of dominated alternatives in the short lists	Number of alternatives in the short lists										
	1	2	3	4	5	6	7	8	9	10	sum
0	0	0	1	0	1	0	-*	–	–	–	2
1	0	0	1	3	4	0	1	-*	–	–	9
2	–	0	2	4	4	3	1	1	1*	–	16
3	–	–	0	0	0	1	1	2	2	-*	6
4	–	–	–	0	0	1	1	1	2	5	10
5	–	–	–	–	0	0	0	0	1	1	2
6	–	–	–	–	–	0	0	0	0	0	0
7	–	–	–	–	–	–	0	0	0	0	0
8	–	–	–	–	–	–	–	0	0	0	0
9	–	–	–	–	–	–	–	–	0	0	0
10	–	–	–	–	–	–	–	–	–	0	0
sum	0	0	4	7	9	5	4	4	6	6	45

* Non–blank possibility for one subject only

Tables 3 and 4 seem to document little evidence of the hypotheses of the existence of an editing phase and of the elimination of dominated alternatives in the editing phase. If all subjects would have complied with the conditions of the editing phase[53], then we should observe in Tables 3 and 4 nonzero entries only in the first seven (six for Table 4) columns of line 1, which would then, of course, be replicated in the sum line. This means that the hypotheses of the existence of an editing phase and the elimination of dominated alternatives are for the first part of the experiment only consistent for 15.56% ($\frac{7}{45}$) and for the second part only for 4.44% ($\frac{2}{45}$) of all subjects.

We can also have a look at the percentages of subjects whose short lists do not exceed the number of undominated alternatives. This gives us rates of 64.44% ($\frac{29}{45}$) for the first part and 55.56% $\frac{25}{45}$) for the second part of the experiment. However, this does

[53]Remember that this means that the short lists should not exceed the set of undominated alternatives and all undominated alternatives should be eliminated from the short lists.

not explain the occurrence of dominated alternatives even within this restricted set of short lists. We can perhaps interpret it as subjects' inability to correctly identify any undominated alternative.

On average, we observe close to 2 dominated alternatives in the average short list in part one, and close to 2.5 dominated alternatives in the average short list of part two of the experiment. No wonder that applying a Mann–Whitney U–test[54] to test the null hypothesis of the marginal distribution $(1, 0, 0, \ldots, 0)$ against the actual distributions of the right margins of Tables 3 and 4 rejects the null hypothesis at the 1% significance level.

This provokes, of course, the question of the *intensity* of rejecting the editing hypothesis. Table 5 informs us about this.

Table 5: k–dominated Alternatives in the Short Lists

	Total number of alternatives in the short lists	0–dominated alternatives ($k = 0$)		1–dominated alternatives ($k = 1$)		k–dominated alternatives ($k \geq 2$)	
		number	%	number	%	number	%
Part I	282	193	68.44	76	26.95	13	4.61
Part II	289	178	61.59	95	32.87	16	5.54

Table 5 shows us that the intensity of the rejection of the hypothesis of the existence of an editing phase and the elimination of dominated alternatives is modest. 68.44% [61.59% in part two] of all alternatives in the short lists are undominated alternatives and more than 94% of all alternatives in the short lists are made up of undominated or 1–dominated alternatives. These percentages may as well be interpreted as conditional probabilities that a choice alternative is undominated *given* that it is a member of a short list. The conditional probabilities are 0.6844 for the first and 0.6159 for the second part of the experiment. The respective pure chance probabilities that an alternative happens to be undominated is 0.28 ($\frac{7}{25}$) for the first part of the experiment and 0.26 ($\frac{6}{23}$) for the bulk of the second part of the experiment. These figures lie well below the conditional probabilities, which demonstrates that undominated alternatives loom larger in the subjects' considerations than dominated alternatives.

The figures shown in Table 5 could indicate that, although subjects aim at eliminating dominated alternatives from their short lists, their discrimination between dominated and undominated alternatives is somewhat imperfect, which could then explain that 1–dominated alternatives count for about one fourth to one third of all alternatives in the short lists[55]. Juxtaposing undominated alternatives in the short lists to k–dominated alternatives ($k \geq 1$) gives us 31.56% misperformances for the first part of the experiment.

[54]Cf., e.g., Mood, Graybill, and Boes (1974), 522ff.

[55]Notice that subjects' performance deteriorates in the second part of the experiment.

Although this figure is rather high, it is surprisingly close to Camerer's 31.6% error rate[56]. If we allow for an error rate of 25%, this means that more than 90% of our subjects would truly comply with the editing hypothesis, but were prevented by their natural error rate from accomplishing this goal.

Concerning the second part of the experiment, our subjects' performance deteriorated. Now 38.41% of k–dominated alternatives were in the short lists. Allowing an error rate of 25%, this gives still a moderate inconsistency with the editing hypothesis of 13.41%.

Let us now look at the choices made and at the same time check whether the first, second (and third) best alternatives were contained in the short lists. The data is displayed in Table 6.

Table 6: Structure of the Choices Made

	Total number of cases	First best alternatives		Second best alternatives		Third best alternatives	
		undom	in SL	undom	in SL	undom	in SL
Part I	45	45	45	42	43	38	40
Part II	45	43	45	43	45	–	–

It shows that some 85% of all choices, taking all five choices in a line, are contained in the short lists. Considering $45 \times 5 = 225$ actual choice acts, the hit rate increases to some 97% of choices being in the short lists. This perfomance shows an improving pattern: In the second part of the experiment, 100% of all actual choices were contained in the short lists. We find, however, decreasing fractions of undominated alternatives as the best choices when previously chosen alternatives became irrelevant[57]. For instance, in the first part of the experiment after two consecutive choices the best choices of the remaining alternatives shrink to some 84% undominated alternatives only[58].

4.2 Testing Various Decision Rules

4.2.1 Testing the Conjunctive Rule with Endogenous Cutoff Scores

As a good secretary should satisfy good standards of all relevant attributes, and as the disjunctive rule has performed rather unsatisfactorily in other empirical research[59], we shall restrict our interest to the conjunctive rule and to various lexicographic rules among the noncompensatory decision rules. This section considers the conjunctive rule. Rather than pretending that some minimum attribute levels have been forced upon the decision maker by some outside authority[60], we are taking up Dawes' suggestion of deriving the

[56] Camerer (1989), 81.

[57] Notice that our calculations considered, of course, the changing patterns of undominated alternatives as previously chosen alternatives become unavailable.

[58] This influence of chosen alternatives which become irrelevant is studied in another paper.

[59] Cf. Einhorn (1970; 1971). We shall see below (Section 4.2.6) that the maximax rule, which is closely related to the disjunctive rule, performs equally poor.

[60] This was the way Wright and Barbour (1977) modelled the screening phase of their experiment.

cutoff scores of the attributes endogenously[61], following from the decision maker's goal to whittle down the choice set to a desired number of alternatives which should remain in the short list for further evaluation. This method can be used to determine a subject's short list of choice alternatives (and thus model the subject's editing phase) as well as to determine his ultimate choice if he intends to employ the conjunctive rule right to the end of his decision process.

Let us illustrate the latter case for 25 choice alternatives and 6 attributes. If the subject rates all attributes equally and wants to select *exactly one* in 25 alternatives according to a conjuctive rule, then he will determine the cutoff scores of the attributes endogenously from the formula

$$p^6 = \frac{1}{25} \Rightarrow p = 25^{-\frac{1}{6}} = 0.5848 \ .$$

This means that the cutoff scores begin for each attribute after the 58.48% best attribute values and eliminates the 41.52% of the alternatives with the worst attribute values. Proceeding sequentially, this leaves the decision maker with exactly

$$25 \times (0.5848)^6 \approx 1$$

choice alternative left. Proceeding along these lines, we find the cutoff scores for six equally rated attributes and 22 to 24 alternatives (i.e., for all option sets arising in our experiments) from[62]:

$$\begin{array}{lllll} p^6 & = & \frac{1}{24} & \Rightarrow & p_{(24)} & = & 0.5888; \\ p^6 & = & \frac{1}{23} & \Rightarrow & p_{(23)} & = & 0.5930; \\ p^6 & = & \frac{1}{22} & \Rightarrow & p_{(22)} & = & 0.5974. \end{array}$$

The cutoff scores are then gained from the acceptance of the best $ip_{(i)}$ $(i = 22, 23, 24, 25)$ values of the respective attribute values.

Suppose now that the subject has a strict order of the attributes, say $d_1 \succ d_2 \succ d_3 \succ d_4 \succ d_5 \succ d_6$. Everything else remaining the same, we can model this as

$$p^{21} = \frac{1}{25} \Rightarrow p = 25^{-\frac{1}{21}} = 0.858 \ .$$

This gives for the various attributes:

$$\begin{array}{lllll} p_1 & = & p^6 & = & 0.399; \\ p_2 & = & p^5 & = & 0.465; \\ p_3 & = & p^4 & = & 0.542; \\ p_4 & = & p^3 & = & 0.631; \\ p_5 & = & p^2 & = & 0.736; \\ p_6 & = & p^1 & = & 0.858. \end{array}$$

[61] Dawes (1964), 105ff.

[62] If necessary, we indicate the number of alternatives, to which the cutoff probability refers, in brackets.

The cutoff score for the first attribute begins after the best 39.9% attribute values and ends for the sixth attribute close after the best 85.8% attribute values. This reflects that the subject is more demanding with respect to more important attributes requiring higher cutoff scores. Suppose the chosen alternative becomes invalid. Then, for the next step of the decision, this procedure has to be repeated for 24 choice alternatives, etc.

If the subject wants to whittle down his choice set to 10 alternatives (forming then his short list resulting from the editing phase) by means of a conjunctive rule, then he derives his cutoff scores from the formula

$$p^6 = \frac{10}{25} \Rightarrow p = 0.858 ,$$

if the subject rates all attributes equally.

Alas, tempting as this model of a conjunctive rule looks, this procedure is not immune to path–dependency. The short list or the ultimately chosen alternative may well depend on the order in which the various attributes are screened. Therefore, sensitivity analyses (applying different orders of screening the attributes) are expedient in cases of equally rated attributes. In cases of a preference order of attributes, this provides a natural sequence for the screening of attributes.

The path–dependency caused excessive computational effort. For a single decision of a subject with equally rated attributes we had to calculate $6! = 720$ combinations. This is easily seen: We can start with each of the six attributes, continue with each of the five remaining attributes etc., until we have checked all 720 combinations. As this procedure has to be applied to all of a subject's five decision, we had to calculate $3,600$ combinations of a single subject with equally rated alternatives. This immense computational effort induced us to confine ourselves to investigate the conjunctive rule only for the actual choice taken, rather than investigating also the short lists.

Whenever a subject chooses an alternative which is at the same time also an element of an optimum combination, this subject scores a hit. Table 7 summarizes the data gained from investigating Dawes' conjunctive rule.

Table 7 reports the structure of hits at all five decisions (denoted by D_1 to D_5) made. 1 denotes a hit according to the conjunctive rule, 0 signals that the subject failed to make his or her decision according to the conjunctive rule. All hit combinations which did not actually occur were, of course, deleted from Table 7. D_1 to D_3 concern the first part of the experiment, D_4 and D_5 the second. Allowing for at most one error in five decisions, we see that the choice behaviour of some 20% of our subjects can be modelled according to Dawes' conjunctive rule.

Table 7 also reveals some interesting relationships about conditional probabilities. For instance, out of the 15 subjects which conformed at least twice with the conjunctive rule in the first part of the experiment, 12 conformed with the conjunctive rule for their first choice in part two, and 7 conformed for both choices in part two with the conjunctive rule. This gives conditional probabilities[63] of 0.8 and 0.47 respectively. This shows again that a group of subjects look as if they acted in conformity with the conjunctive rule.

[63]The condition being that the subject conformed at least twice with the conjunctive rule in the first part of the experiment.

Table 7: Conformity with the Conjunctive Rule

Number of Hits	D_1	D_2	D_3	D_4	D_5	Frequency	%	
0	0	0	0	0	0	5	11.11	11.11
1	1	0	0	0	0	8	17.78	
	0	1	0	0	0	4	8.89	
	0	0	0	1	0	1	2.22	
	0	0	0	0	1	1	2.22	31.11
2	1	0	1	0	0	1	2.22	
	1	0	0	1	0	3	6.67	
	1	0	0	0	1	2	4.44	
	0	1	1	0	0	1	2.22	
	0	0	1	1	0	2	4.44	
	0	0	1	0	1	2	4.44	24.43
3	1	1	0	1	0	2	4.44	
	1	0	1	1	0	1	2.22	
	1	0	1	0	1	1	2.22	
	1	0	0	1	1	2	4.44	13.32
4	1	1	1	1	0	2	4.44	
	1	1	0	1	1	2	4.44	
	1	0	1	1	1	1	2.22	11.10
5	1	1	1	1	1	4	8.89	8.89
Sum						45	100	100

Table 8 informs on the hit rates at different decision orders. We see that the hit rates are markedly higher whenever the decision problem is analyzed from scratch (first and fourth decisions) and is thus unadulterated from the frustrating experience of past choices which had become invalid.

Table 8: Hit Rates at Different Decision Orders

Decision Order	Number of Hits	Hit Rate
First decision	29	64.44%
Second decision	15	33.33%
Third decision	15	33.33%
Fourth decision	20	44.44%
Fifth decision	15	33.33%

4.2.2 Testing the Elimination–by–Aspects Rule

Recall that Tversky (1972a,b) modelled the elimination–by–aspects rule in the framework of stochastic choice theory. Our experimental design, which presents a certain choice situation only once to a subject (and does not generate data on the full preference orderings of all alternatives) does not allow calculations as required by these decision rules. However, their more basic message seems to be attractive enough to try our best to test them in some rudimentary forms applicable to our data. We can, for instance, apply a between–subjects analysis and look for some positive correlation between the attractiveness of alternatives and the number of other alternatives which they dominate[64], or we can apply some other pattern elimination processes.

Starting with the second approach, we test the elimination–by–aspects rule using an algorithm which gradually lowers the attribute values and checks at each step whether some of the actual alternatives dominates these sham vectors. To illustrate, the first sham alternative is composed by the best attribute values in each row of Table 1, viz.

$$(120, 90, 95, 10, 10, 10) \ .$$

Of course, no alternative dominates this vector. Then we compose a sham vector using the second best values of all attributes. This gives:

$$(118, 88, 92, 9, 9, 9) \ .$$

Again, no alternative dominates this vector. The next vector constructed in this way is the alternative a_{13}, which places this alternative at the top. Proceeding further in this way, we arrive after some other sham vectors at the sham vector

$$(104, 73, 72, 5, 4, 4) \ ,$$

which is dominated by alternative a_9. Applying this algorithm further gives us for the top five items the preference order:

$$a_{13} \succ a_9 \succ a_{10} \succ a_1 \succ a_{22} \ .$$

Table 9 examines the performance of the top three alternatives in part one of the experiment.

Table 9: The Performance of a_{13}, a_9, and a_{10}

$a_{13} \succ a_9 \succ a_{10}$	9 times chosen
$a_{13} \succ a_9$ at top	15 times chosen
a_{13}	37 times first; 5 times second; 1 time third

This result is very appealing. Table 9 shows us that the ordering of choices $a_{13} \succ a_9 \succ a_{10}$ emerged in 20% of all responses. If all 25 alternatives are considered, this preference ordering would evolve by chance only with a probability of $0.000072464 = 7.2464 \times 10^{-5}$.

[64]Cf. Tversky (1972a), 295, to see that this is a valid interpretation of the elimination–by–aspects hypothesis. Many other scholars, too, have found empirical evidence that the addition of dominated alternatives increases the attractiveness of the now dominating alternatives. Cf., e.g., Huber, Payne, and Puto (1982); Huber and Puto (1983); Tyszka (1983); Ratneshwar, Shocker, and Steward (1987); Wedell (1991).

If only the first thirteen alternatives are taken as eligible, it still can arise only with a probability of $0.00058275 = 5.8275 \times 10^{-4}$. The ordering $a_{13} \succ a_9$ at top was chosen in one third of all responses. Considering all 25 alternatives, it would evolve by chance only with a probability of $0.0016667 = 1.6667 \times 10^{-3}$. If only the first thirteen alternatives are considered as eligible, the ordering $a_{13} \succ a_9$ at top arises only with a probability of $0.0064102 = 6.4102 \times 10^{-3}$. This shows that the elimination–by–aspects rule provides a rather good forecast of subjects' actual choices.

The second part of the experiment was tested separately, because, as a consequence of error, subjects may have failed to realize $a_{13} \succ a_9 \succ a_{10}$ in the first part of the experiment. Starting their decision process from scratch in the second part of the experiment may turn out to be more successful. Yet the choice situations may well be different. Therefore, we used the above algorithm to individually compute the best alternatives under an elimination–by–aspects rule and ask whether the subjects indeed followed the respective orders, say $a_i \succ a_j$. This is summarized in Table 10.

Table 10: The Performance of the Best Alternatives in Part Two

$a_i \succ a_j$	8 times chosen
a_i at top	22 times chosen
a_i second	11 times chosen

This shows again results which are far above the realizations which would evolve from pure chance.

Another way to test the elimination–by–aspects rule is to explore the correlation between the attractiveness of alternatives (in terms of actual choices) and the number of alternatives which they dominate. For the first choice in the first part of the experiment, we have no problems, because all subjects are faced with the same option set. Correlating thus the actual choices of the various alternatives against the number of the alternatives which they dominate gives a correlation coefficient of 0.6037319.

One might surmise that this high correlation coefficient is influenced by the fact that a_{13} was chosen 37 times as the first best choice, and a_{13} dominates 12 other choice alternatives. Therefore, we calculated another correlation coefficient, taking the 37 subjects who had chosen a_{13} as their first best alternative as a basis. These 37 subjects all faced the same option set for their second best choice. Correlating their second best choices against the number of alternatives which they dominate yields a correlation coefficient of 0.6035214, which is nearly equal to the former correlation coefficient.

Things become more complicated for the second part of the experiment, because subjects face different decision problems. We tried to allow for this by weighting alternatives for their availability. For instance, a_{13} was only available for three subjects in part two and was chosen two times. This gives a ratio of $\frac{2}{3}$. Weighting this for availability gives $\frac{2}{3} \times 45 = 30$. That is, we pretend that a_{13} would have been chosen by 30 subjects if it were available for all subjects. This procedure is not entirely satisfactory, as it feigns that there was a fictitious choice involving (as this procedure works out) some 80 subjects instead of 45, but, as a correlation coefficient normalizes the figures anyway, we thought that we should try this approach. We find a correlation coefficient of 0.8215491.

These results show that we observe a distinctly positive correlation between the attractiveness of an alternative (in terms of actual choice) and its number of dominated other alternatives.

With respect to our results we are entitled to say that the choice behaviour of at least 20% of our subjects is consistent with the elimination–by–aspects rule.

4.2.3 Testing the Prominence Hypothesis

There seems to be no clearcut recommendation as to how to test the prominence hypothesis in a multiattribute decision problem with K attributes for $K > 2$.[65] We are trying a rank correlation between the alternatives in the short lists and indicated ranks of the attributes.

As logit and probit do not yield significant estimates, we employ a linear probability model of the alternatives in the short lists and the order of the attributes as indicated by the subjects. The linear probability model is derived from

$$\pi_i = \beta_0 + \sum_{k=1}^{6} \beta_k \, \hat{a}_{ik} + \varepsilon_i \ ,$$

where π_i is accorded the value 1 if alternative i was a member of the short list, and 0 otherwise. The β_k's represent the weights of the standardized attribute values

$$\hat{a}_{ik} := \frac{a_{ik} - \min_j\{a_{jk}\}}{\max_j\{a_{jk}\} - \min_j\{a_{jk}\}} \ ,$$

β_0 denotes a constant, and ε_i denotes the error term. Because of heteroscedascity of the error term we employed a two–stage Aitken (weighted least squares) estimation for the β_k's (deleting alternatives for which $\pi_i^{est} \notin [0,1]$ after the first stage of the estimation)[66]. Then all β_k's which did not satisfy the 5% significance level were eliminated (i.e., set equal to zero). The remaining β_k's were then transformed into ranks, treating β_k's which did not differ by more than 5% as identical. For identical coefficients, a mid–ranking procedure was applied. Then we computed Spearman's rank correlation coefficients for the ranks of the attributes derived in this way and the ranks of the attributes as indicated by the subjects. This gave us two rank correlation coefficients for each subject, one for the first part and one for the second part of the experiment.

The result is not particularly encouraging. The rank correlation coefficients do not point strongly in anyone direction. We observe positive, negative, and near–zero rank correlation coefficients. The average rank correlation coefficient is 0.3003 for the first part and 0.3625 for the second part of the experiment. Using these two sets of 45 individual rank correlation coefficients to compute the ordinary (Bravais–Pearson) correlation coefficient, we get a value of 0.0118, which means that there is hardly any correlation between

[65] Tversky, Sattah, and Slovic (1988), 388.

[66] Cf. Goldberger (1964), 249f.; Gujarati (1988), 468–473.

the rank correlation coefficient of the first and the second part of the experiment. Thus, the rank correlation analysis rejects the prominence hypothesis.

We also tried out two other methods to test the prominence hypothesis with similarly poor results. Therefore, we refrain from reporting them here[67].

4.2.4 Testing the Majority Rule

The majority rule asserts that subjects form their preferences on choice alternatives by pairwise comparisons, simply counting the attributes in favour of one or the other. If we have an equal number of attributes in favour of either of two alternatives, the majority rule indicates indifference. Let us code $a_i \succ a_j$, i indicating the line and j the column of an adjacency matrix, by 1, $a_i \sim a_j$ by 0, and $a_i \prec a_j$ by a hyphen, we can form the priority structure of the majority rule in Table 11, which corresponds to Table 2 for the dominance structure. From Table 11, we immediately see that, neglecting ties, three alternatives form the unrivalled winners in the order $a_{13} \succ a_9 \succ a_{10}$, which compares favourably with our test of the elimination–by–aspects rule. Furthermore, we see that the majority rule is plagued by so many intransitivities, that any subject would simply be lost without having the powerful instrument of an adjacency matrix at hand.

Therefore, we confined ourselves to testing our subjects' internal inconsistencies of their actual choices. Suppose, for instance, that a subject's preferences for alternatives, as revealed by his actual choices, are $a_1 \succ a_2 \succ a_3$ for the first part of the experiment. Denoting weak priority under a majority rule (preference or indifference) by R and strict priority by P, we should expect $a_1 \mathrm{R} a_2 \mathrm{R} a_3$ if the majority rule is indeed followed. Comparing these two orders, the first one being given, we could find up to three priority violations for part one of the experiment. For instance,

$$a_1 \mathrm{R} a_2,\ a_3 \mathrm{P} a_2,\ a_1 \mathrm{R} a_3$$

means exactly one priority violation. Table 12 lists the priority violations observed in our experiment.

It is interesting to find some structure in the priority violations of the majority rule. A probit analysis shows that the subjects with more priority violations in the first part of the experiment exhibit a greater tendency for priority violations in the second part of the experiment[68]. Moreover, this tendency increases with a rising number of priority violations in the first part of the experiment. As to our notation, X denotes the number of priority violations in the first part of the experiment, and $\Phi(\alpha + \beta X)$ gives us the probability of a priority violation in the second part of the experiment given X priority violations in the first part of the experiment, where Φ denotes the standard normal distribution function. Table 14 shows that the probability of a priority violation in part two is an increasing function of the number of priority violations in part one of the experiment.

[67] Einhorn, too, failed to discover a marked relationship between the ratings of attributes and subjects' decisions. Cf. Einhorn (1971), 17: "The ratings of importance for each subject for each attribute were collected and analyzed. Unfortunately, there was no consistent pattern of use for any particular variable".

[68] Notice, however, that the coefficient β in our probit estimate is significant only at the 7% level.

Table 11: Priority Structure of the Majority Rule

/	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	0	1	0	0	0	0	0	1	-	-	1	1	-	1	1	1	1	1	1	1	1	0	1	1	1
2	-	0	-	-	-	-	-	0	-	-	-	-	-	1	1	0	0	0	1	1	1	-	0	1	1
3	0	1	0	1	0	1	0	1	-	-	1	1	-	1	1	1	1	1	1	1	1	1	1	1	1
4	0	1	-	0	-	0	0	1	-	-	1	1	-	1	1	1	1	1	1	1	1	1	1	1	1
5	0	1	0	1	0	1	-	-	-	-	-	-	-	1	1	1	1	1	1	1	1	0	1	1	1
6	0	1	-	0	-	0	-	-	-	-	-	-	-	1	1	0	1	1	1	1	1	-	1	1	1
7	0	1	0	0	1	1	0	1	-	-	-	-	-	1	1	1	1	1	1	1	1	1	1	1	1
8	-	0	-	-	1	1	-	0	-	-	-	-	-	-	1	1	1	1	1	1	1	-	1	1	1
9	1	1	1	1	1	1	1	1	0	1	0	0	-	1	1	1	1	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	-	0	0	0	-	1	1	1	1	1	1	1	1	1	1	1	1
11	-	1	-	-	1	1	1	1	0	0	0	1	-	1	1	1	1	1	1	1	1	1	1	1	1
12	-	1	-	-	1	1	1	1	0	0	-	0	-	1	1	1	1	1	1	1	1	1	1	1	1
13	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
14	-	-	-	-	-	-	-	1	-	-	-	-	-	0	1	1	1	0	1	1	1	-	0	1	1
15	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	-	-	1	0	1	-	-	-	-
16	-	0	-	-	-	0	-	-	-	-	-	-	-	-	0	0	1	0	1	1	1	-	1	1	1
17	-	0	-	-	-	-	-	-	-	-	-	-	-	-	1	-	0	0	1	1	1	-	0	0	1
18	-	0	-	-	-	-	-	-	-	-	-	-	-	0	1	0	0	0	1	-	1	-	-	0	-
19	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	-	-	-	-	1
20	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	-	-	1	0	0	1	-	-	1	-
21	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	0	-	-	1	-
22	0	1	-	-	0	1	-	1	-	-	-	-	-	1	1	1	1	1	1	1	1	0	1	1	1
23	-	0	-	-	-	-	-	-	-	-	-	-	-	0	1	-	0	1	1	1	1	-	0	0	1
24	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	0	0	1	-	-	-	0	0	0
25	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-	1	-	1	1	-	-	0	0

Table 12: Priority Violations of the Majority Rule

	Priority violations			
	0	1	2	3
Part I	22	22	1	0
Part II	32	13	–	–

Table 13: Probit Estimates for the Majority Rule

Label	α	β
Coeff.	-0.9622	0.6946
Std.Error	0.3084	0.3825
t–Stat.	-3.1199	1.8159
Level of Sign.	0.0018	0.0694

Table 14: Conditional Probabilities of Priority Violations in Part Two

X	0	1	2	3
$\Phi(\alpha + \beta X)$	0.1685	0.3936	0.6664	(0.8686)

This obviously suggests that we have two rather stable cohorts among our subjects. One cohort seems to make consistent use of the majority rule, whereas the other cohort does not seem to pay particular attention to it. This conjecture is confirmed by Table 15 which shows the violations of the majority rule.

Table 15: Violations of the Majority Rule

Number of Violations of the Majority rule		Frequency		Conditional Probabilities, given n Violations in Part One		
in part one	in part two	numbers of subjects	%	$n = 0$	$n = 1$	$n = 2$
0	0	18	30.0	0.8182	–	–
0	1	4	8.9	0.1818	–	–
1	0	14	31.1	–	0.6364	–
1	1	8	17.8	–	0.3636	–
2	1	1	2.2	–	–	1.0

Table 15 corresponds pretty well to the results of Table 14. The conditional probabilities of a violation of the majority rule in part two, given no violation in part one, are 0.1685 (Table 14), and 0.1818 (Table 15). For one violation in part one the respective probabilities are 0.3936 (Table 14), and 0.3636 (Table 15). For two violations in part one we have 0.6664 from Table 14, and 1.0 from Table 15. Moreover, Table 15 shows us that 30% of our subjects exhibit a behaviour which is fully consistent with the majority rule.

4.2.5 Insufficient Data Base to Test the Linear and the Multiplicative Multiattribute Utility Rules

Any experimenter must accept compromises when conducting an experiment. Testing the linear multiattribute utility rule

$$\sum_{k=1}^{K} w_k v_k(a_{ik})$$

and the multiplicative multiattribute utility rule

$$\prod_{k=1}^{K} [1 + \lambda w_k v_k(a_{ik})]$$

requires a special experimental design which is attuned to this task.

First, we would have to test for mutual preference independence [for the linear rule] or for weak difference independence [for the multiplicative rule] of the attributes[69]. These conditions warrant that the $v_k(\cdot)$–functions can be evaluated independently of the values of all other attributes. If an experiment shows serious violations of these requirements, then the linear and/or the multiplicative multiattribute utility rule do not apply.

If the independence requirement is met, the $v_k(\cdot)$–functions and the weights w_k have to be elicited. The $v_k(\cdot)$–functions can be derived either by methods of numerical estimation (direct rating, category estimation, ratio estimation, curve drawing), or by methods employing indifference relations (difference standard sequence, bisection, dual standard sequence, sequential trade–off). The weights, too, can be derived either by methods of numerical estimation (ranking, direct rating, ratio estimation, swing weights) or by using

[69] For details cf. Dyer and Sarin (1979), 812–815; Keeney (1974).

indifference relations (cross–attribute indifference, cross–attribute strength of preference). Selected combinations of deriving the $v_k(\cdot)$–functions and the weights w_k have been given special names, such as SMART (simple multiattribute rating technique), difference value measurement, conjoint measurement, weak–order model, etc.[70]

Our data base contains just our subjects' rankings of attributes, which can be put to good use to derive the weights w_k, but we have no data whatsoever to derive the $v_k(\cdot)$–functions. The data requirements to derive $v_k(\cdot)$–functions for six attributes are indeed formidable and require experiments which focus entirely on this task. Although our data base allows testing several multiattribute decision rules, it is decisively insufficient to test the linear or the multiplicative multiattribute utility rules[71].

We also considered making use of the independent multinomial logit model, which has been used in the analysis of brand choice behaviour. This approach estimates the weights w_k from

$$P(a_i \mid A) = \frac{\exp(\sum_{k=1}^{K} w_k a_{ik})}{\sum_{j=1}^{n} \exp(\sum_{k=1}^{K} w_k a_{jk})} \ ,$$

where $P(a_i \mid A)$ denotes the probability that the choice alternative a_i is chosen from the set of alternatives A.[72] However, this approach assumes that the subjects are homogeneous and behave in accordance with the random utility model. As our subjects exhibit rather diverse rankings of the attributes, common attribute weights for all subjects would come up to a gross misspecification of the choice model. Therefore, we did not consider the independent multinomial logit model as a serious candidate to mimick the linear multiattribute utility rule. It may be appropriate as a description of brand choice, but not for multiattribute choices in general.

4.2.6 Testing the Maximin and Maximax Rules

Following Einhorn (1970; 1971), we approximate the maximin rule as

$$\prod_{k=1}^{6} (\alpha_{ik})^{\beta_k} \ ,$$

and the maximax rule as

$$\prod_{k=1}^{6} \frac{1}{(c - \alpha_{ik})^{\beta_k}} \ .$$

The α_{ik}'s are the values of the attributes of the various choice alternatives, normalized on the unit interval. The exponents β_k were derived from the subjects' attribute rankings in

[70] For details cf. von Winterfeldt and Edwards (1986), chapters 7 and 8; Keeney and Raiffa (1976), chapter 3.

[71] Meyer and Johnson (1995), G183f., report a poor performance of the linear multiattribute utility rule.

[72] Cf., e.g., Manrai (1995), 5.

the following way. For indifference between all attributes we used $\beta_k = \frac{1}{6}\ \forall\ k = 1, 2, \ldots, 6$. For strict preference orderings, we used $\frac{6}{21}$ as an exponent for the highest ranked attribute, $\frac{5}{21}$ as an exponent for the second highest ranked attribute, etc., ending with $\frac{1}{21}$ for the last ranked attribute. If we have, for instance, one attribute at the highest rank, three attributes second ranked, and two attributes at the third rank, we applied the exponents $\frac{3}{11}$ for the highest ranked attribute, $\frac{2}{11}$ for each of the three second ranked attributes, and $\frac{1}{11}$ for each of the two third ranked attributes. These examples should suffice to clarify the rule of construction of the exponents.

Table 16 informs on the compliance of subjects' responses with the maximin rule. It reports the structure of hits at all five decisions (denoted by D_1 to D_5) made. 1 denotes a hit according to the maximin rule, 0 a failure to comply with the maximin rule. All hit combinations which did not actually occur were deleted. D_1 to D_3 concern the first part of the experiment, D_4 and D_5 the second.

Table 16: Subjects' Choices Following the Maximin Rule

Number of Hits	D_1	D_2	D_3	D_4	D_5	Frequency	%	Group %
	1	0	0	0	0	5	11.11	
1	0	1	0	0	0	2	4.44	
	0	0	1	0	0	1	2.22	
	0	0	0	1	0	2	4.44	22.22
	1	1	0	0	0	2	4.44	
	1	0	1	0	0	2	4.44	
2	1	0	0	1	0	3	6.67	
	1	0	0	0	1	4	8.89	
	0	1	0	1	0	1	2.22	
	0	1	0	0	1	1	2.22	28.89
	1	1	0	1	0	4	8.89	
	1	1	0	0	1	2	4.44	
3	1	0	1	1	0	5	11.11	
	1	0	1	0	1	1	2.22	
	0	1	1	1	0	1	2.22	28.89
	1	1	1	1	0	5	11.11	
4	1	1	1	0	1	4	8.89	20.00
SUM						45	100.00	100.00

Table 16 shows that, while 20% of our subject acted in conformity with the maximin rule in the first part of the experiment, not a single subject acted for both choices in the second part of the experiment in conformity with the maximin rule. Thus, it seems that the conformity of agents' choices with the maximin rule decreases as the experiment continues.

How can subjects' compliance with the maximin rule be evaluated when we allow for some error, e.g. missing the maximin rule by just one alternative. Table 17 informs about this.

Table 17: Compliance with the Maximin Rule

Actual Choices	Chosen alternative complies with maximin rule	Chosen alternative is second best according to maximin rule	Chosen alternative ranks lower than second best according to maximin rule
1st	37	3	5
2nd	22	10	13
3rd	19	10	16
4th	21	11	13
5th	12	12	21

Table 17 shows that, allowing for an error of missing the best alternative according to the maximin rule but by one alternative, we have a hit rate (except the 5th choice) of more than 64%. Thus, although the maximin rule is not followed for all of a subject's choices, our data show that this rule generally enjoys great attention among our subjects.

In contrast, things are not very encouraging for the maximax rule. The maximax rule involves the choice of the parameter c, where $c > 1$. Our calculations show us that the choice alternatives endorsed by the maximax rule are extremely sensitive to the value of c. For $c = 1.05$, only 9 subjects are in conformity with the maximax rule for the first choice of part one of the experiment. This figure rises to 15 for $c = 1.1$, and to 26 for $c = 1.2$. The hit rate increases sharply with rising c, which reflects that greater values of c reduce the differences between the choice alternatives by assigning the same maximum value to more alternatives. Therefore, we conclude that the maximax rule is not a good explanation of individual behaviour and we do not bother the reader with numerical results of our tests of this rule.

5 Conclusion

We utilized a choice experiment presented in the context of recruiting a secretary to investigate whether decision processes are multi–phased and which decision rules are consistent with subjects' choice behaviour. In the most elementary form, mulit–phased decision processes should manifest at least in the form of an editing phase, in which dominated alternatives are eliminated from further consideration, and a decision phase proper. Furthermore, we tested whether individual choice behaviour is consistent with various decision rules which were surveyed in Section 2.2.

We have found that, applying a *strict* yardstick, the existence of an editing phase and the elimination of dominated alternatives is not confirmed. We observed an average of more than two dominated alternatives in the short lists and rejection rates of more than 60%. However, the intensity of rejecting the existence of an editing phase and the elimination of dominated alternatives is modest. 60% and more of all alternatives in the short lists are undominated alternatives and more than 94% of all alternatives in the short lists are either undominated or 1–dominated alternatives. Allowing for an error rate of some 25% implies that some 90% of our subjects would truly comply with the editing hypothesis, a picture which is only obscured by their natural error rates.

As to the testing of decision rules, we tested the conjunctive rule with endogenous cutoff scores, the elimination–by–aspects rule, the prominence hypothesis, the majority rule, and the maximin and maximax rules.

The conjunctive rule was tested using endogeneously determined cutoff scores to determine the subjects' ultimate choices. We found that some 20% of our subjects seem to consistently apply the conjunctive rule for their ultimate choices.

We tested the elimination–by–aspects rule using an elimination algorithm which provided us with preference orderings of alternatives. These fitted surprisingly well. Their good performance ranks far above the random choice probabilities, which means that the behaviour of a substantial part of our subjects is consistent with the elimination–by–aspects rule. Trying correlations between chosen alternatives and the numbers of the alternatives which they dominate (another proxy for the elimination–by–aspects rule) provided encouraging results, too.

In order to test the prominence hypothesis, we employed a linear probability model applied to the alternatives in the short lists. Then, for each subject, we computed Spearman's rank correlation coefficient between the ranks of the attributes derived in this way and the ranks of the attributes as indicated by the subjects. Our results suggest a rejection of the prominence hypothesis.

The majority rule, on the other hand, has a remarkably good performance. For the first part of the experiment, it yields the same top ranked alternatives in the order $a_{13} \succ a_9 \succ a_{10}$ as the elimination–by-aspects rule and, thus, shares its good performance. Moreover, we found evidence that our subjects split into two cohorts, one complying with the majority rule and the other one disregarding it.

The maximin rule did remarkably well. Allowing for a natural error to miss the best alternative but by one alternative gave us a hit rate of more than 64%. The maximax rule, in contrast, provided rather discouraging results and should, therefore, be discarded.

This shows that our experiment has shed light on the existence of an editing phase and on the spread of using various multiattribute decision rules.

6 References

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